Short Paper #2: Proposing an Observational Study

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1 Research question

Can inducing curiosity and uncertainty in products attract customers and boost sales?

Theoretically, curiosity and uncertainty are shown to have motivational powers. People are more attracted to options that cause curiosity, even when these options may bring negative feelings (Hsee & Ruan, 2016). Feelings of uncertainty can also boost investment, even when the total expected money gain is less than those without uncertainty (Shen, Fishbach, & Hsee, 2015). However, all these studies are conducted in laboratories. Whether these effects can hold in real world is unknown.

Practically, inducing curiosity and uncertainty may be applied to make products more attractive with few additional investments. Below I will call this strategy as **curiosity promotions**. There could be at least two ways of inducing curiosity and uncertainty in products. The first is to randomly assign customers who order the same products different versions of the products that differ in peripheral, insignificant features. These features could be colors, textures, shapes or scents that do not influence the major function of the products. For example, customers order a bunch of soaps, and there are 3 colors of soaps with exactly same functions in the same brand. If customers can choose which color of the soup they want, there is no inducement of curiosity or uncertainty. Instead, if they are told that colors will be randomly assigned to them, this induces curiosity and uncertainty for them. The second way is random allocation of free gifts instead of the products. Customers are told that they can get free gifts after purchasing the product. In one case the gift is certain (e.g., a pen). In another case, the gift will be randomly determined (e.g., either a pen or a notebook of the same price). The latter can stimulate curiosity and uncertainty. In this study, I will only focus on the first kind of curiosity promotions which will be discussed below.

Curiosity promotions seem to be against our intuition. After all, people should feel more autonomous if they can choose more, and it is more likely to obtain their favourite options. However, there are reasons to think it can work in some contexts. First, there are already too many options to compare and choose from for products. Random assignment on trivial features can save time and computation. Second, customers may not have a clear preference on different versions (e.g., colors of soaps), so they will be equally satisfied with the assignment. Third, customers will be more excited when they wait for receiving the product, as they feel curious about what versions of product or free gifts will be sent. Therefore, chances are that customers like products with curiosity promotions more than those of equivalent quality.

2 Plan for using observational data and research design

I plan to use **Amazon product data** (http://jmcauley.ucsd.edu/data/amazon/). This dataset includes 142.8 million reviews (ratings, text, helpfulness votes), product metadata (descriptions, category information, price, brand, and image features), and links (also viewed/also bought graphs) spanning from May 1996 to July 2014.

The research design is **approximating experiments by matching**.

First, I plan to find products that use curiosity promotions. I will search texts in the descriptions of products to identify those using curiosity promotions. As discussed above, there could be at least 6 combinations: (2: certain vs random) product * (3: without vs certain vs random) free gift. To simplify the situation and make it more feasible, I will only focus on one kind of combination--random products without free gifts, and examine common types of randomization. For example, the searching rule for "color" is containing "random*color" or "color*random"or "color at random" (to name a few, and other possible combinations will be identified after consulting with experts or exploring the searching results containing both "color" and "random"), but containing no "gift" (and its synonyms). Similarly, I will replace the word "color" with other types of randomization repectively: shape, stripe, scent, size, style, pattern and flavor (hyperlinks link to real examples on Amazon, showing that this kind of curiosity promotion is common and the information is identifiable).

Second, I will find fair comparisons of these products. I will primarily match according to the criteria of the same kind of product, similar price and length of descriptions. In addition, I will try many different kinds of matching that may seem to be fair, to boost the compellingness of results. Third, I will compare the sale ranks in the corresponding category, positivity in texts of reviews, and ratings between groups with and without curiosity promotions. Fourth, effects for different categories of items will also be examined, based on the category information in product metadata.

3 Justification

3.1 How does this project illustrate the good characteristics of big data?

Amazon product data are very ideal. Currently Amazon is the largest online retailer (Wahba, 2015), providing very big and representative data. The large size is particularly useful in this study. First, there may not be many products using curiosity promotions. Even when there are, it may not be easy to find many fair comparison groups. Second, it allows making estimates for different subgroups. Matching products in the massive data allows subtle analysis in effects of curiosity promotions in different categories of products. The analysis could give insights just like conducting an enormous number of field experiments, which would have been extremely expensive. Third, it is possible that the effects of curiosity promotions is small, thus it will be hard to obtain with small data. Lastly, the bigness allows multiple groups as possible comparison groups, which can greatly increase our ability to make causal estimates by matching.

Besides, the long span of the data reflects the always-on characteristic. Given the longitudinal data, it is interesting to examine whether effects of curiosity promotions may decline over time (e.g., whether customers may get used to it or not).

Furthermore, they are non-reactive. Most of previous studies on curiosity are conducted in laboratory, where participants may show demand characteristics--an experimental artifact where participants subconsciously change their behavior to fit their guess of the experiment's purpose.

3.2 How this project illustrate the bad characteristics of big data, and how you plan to overcome these weaknesses?

One primary concern is incompleteness and inaccessibility. Especially, they don't provide the exact selling numbers of products but only sales rank. Though sales rank could answer the question, it is at the level of ordinal scale, which means that differences in adjacent ranks can be huge differences in selling numbers. It can be difficult to interpret the effect sizes of curiosity promotions. I will try to contact Amazon to see if I can get access to more sale data of the products involved in comparison. Given that the curiosity promotions may help them make profits, maybe they will provide relevant data.

In tandem with the problem of incompleteness, the lack of demographics data may complicate the problem of drifting. As online markets become more and more popular, it is highly likely that there is a population drift (change in who is using them) over the years. If the effects of curiosity promotions are found to decline over time, it will be hard to clearly attribute it to behavioral drift (change in how people are using them) or population drift. To address this problem, I will break down the time span into several periods to examine the robustness and variations of effects instead of collapsing the years.

What is more, the issue of non-representative should be bear in mind. Customers on Amazon are not a random sample of the population. As online shopping is relatively new, the sample may be younger and richer. Reviews may also be influenced by selection-bias. Some people may contribute lots of reviews, while others rarely write. These limitations will be acknowledged to avoid over-generalization.

In addition, the data might be dirty. Chances are that some reviews are generated by non-human, or are repeated by the same reviewer for multiple times. To avoid being fooled by dirty data, I will perform simple exploratory analysis, and browse sample reviews to check whether there are spams.

Finally, finding appropriate comparison group is critical in matching, and I will try to make the matching as fair as possible. Beyond the criteria I mentioned above for finding comparison group, I will also try many different kinds of matching. For example, I can repeat the analysis including only items on sale within one year, within one month, and contemporaneously with the matched sets, to rule out the influence from seasonal variations.

4 Feasibility assessment of the project as MA thesis

There may be few IRB concerns. The data are publicly available, and are not very sensitive or potentially identifiable.

References

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